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# Sustainable agriculture and farmland productivity nexus in Bangladesh: an empirical study

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# Sustainable Agriculture and Farmland Productivity nexus in Bangladesh: An Empirical Study

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*Abstract:* **This paper employs national aggregated data on the indicators of sustainable agricultural practice in Bangladesh for estimating a multivariate timeseries model that produces plausible simulated outcomes for agricultural land productivity due to 1% change (increase and decrease) in the relevant sustainable agricultural activities. The estimated model has been subjected to a battery of sensitivity analysis and found robust. Plethora of papers exist that have utilized disaggregated primary data for model estimation purpose on this topic. However, authors that have employed national aggregated data claim that these are less susceptible to noticeable human errors and produce better outcomes for policy implications.**

**JEL Classifications: (B16: Quantitative and Mathematical: C22: Time-Series Models, C51: Model Construction and Estimation, C52: Model Evaluation, Validation, and Selection)**

## I. INTRODUCTION

Despite experiencing a declining share in national economic output during recent years, agriculture is a predominant sector of Bangladesh. The sector still provides the largest share of total employment. As of 2017, the agricultural share of total employment stood at 41% compared to 39% of the service and 20% of the industrial sector[1]. More importantly, agriculture absorbs a higher percentage of female labor force than industrial and service sectors. In 2019, agriculture absorbed 58% of female labor force, whereas service and industry engaged 18% and 25% of female labor force in the same year[2]. It may be concluded that agricultural sector plays a significant role in overall labor force employment, as well as, promoting woman empowerment of this nation. On the other hand, Bangladesh is one of the most densely populated countries in the globe and the amount of per capita arable land stood at a meagre 0.05 hectares as of 2018 [4]. Consequently, the nation feels an intensifying stress for increasing agricultural land productivity to ensure food security for its vast population. However, increasing land productivity may not ensure sustainability without which long term agricultural growth will be deterred. Sustainable agricultural practice may apparently seem an unattractive proposition as it requires stringent resource use and deters indiscriminate use of chemical fertilizer and pesticides for short term gain, but this practice is more likely to enhance agricultural productivity over long run. According to the Food and Agricultural Organization (FAO), there are three dimensions of agricultural sustainability, namely, environmental, economic, and social. Sustainability documents of FAO stipulate that farms will be deemed compliant if they attain an acceptable combination of the sub-indicators of sustainable agriculture across these dimensions. As Bangladesh is eyeing on fulfilling the targets of sustainable development by 2030, attaining agricultural sustainability within this timeframe is of prime importance for the nation. At his backdrop, this paper empirically examines if there exists a long run equilibrium relationship between agricultural productivity and other measures of sustainable agricultural practice in Bangladesh. Firstly, the paper attempts to estimate the long run equilibrium relationship between agricultural productivity and some selected measures of sustainable agriculture in Bangladesh using the multivariate time series methodology. Secondly, the paper conducts a simulation analysis by estimating impulse responses of agricultural productivity due to unexpected shocks to the other measures of agricultural sustainability. Unlike many other studies, this paper utilizes national macrolevel data on model variables for the purpose of estimating the long run relationship between the indicators of agricultural sustainability in Bangladesh. All data are procured from the World Development Indicators (WDI) databank that are relatively accurate compared to survey data on individual regions and allows researchers to replicate model estimation for individual country case studies and compare estimation outcomes. This paper finds plausible long run equilibrium relationship between agricultural land productivity and the selected indicators of sustainable agriculture in adherence with relevant literature. In addition, the paper also obtains plausible impulse responses of agricultural productivity due to unexpected shocks to the other indicators of sustainable agriculture. Findings of this paper may have important implications for agricultural policy in Bangladesh.

## II. LITERATURE REVIEW:

In accordance with Food and Agricultural Organization (FAO), sustainable agriculture refers to agricultural activities that comply with the needs of present generations without compromising with those of future generations and simultaneously ensures profitability, environmental health, as well as social and economic equity. There are abundant literal works on agricultural sustainability, but few of them focus on empirical analyses relating to the nexus between agricultural productivity and sustainability. Some of the early works [5] conclude that agricultural activities inflict negative externalities on environment and human health and


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therefore should be controlled either by punitive taxation equivalent to the social damages caused or by ensuring the prudent use of available technology on part of the peasants. However, in the face of rising global population, nations have limited choices left other than increasing food production through intensive agricultural practices that ultimately create environmental unsustainability. Intensive use of chemical fertilizer in Europe has caused the leaching of excess nutrients into water bodies and initiated environmental pollution [16]. This mineral rich inorganic fertilizer is also observed to reduce organic carbon in soil and causes infertility [18]. Reducing excess soil nutrients may have a positive long-term effect on agricultural productivity, soil fertility, and biodiversity [10].

Shortly after independence, Bangladesh faced a rampant food price inflation induced by oil price shock in 1973 and an upsurge in global inflation that followed. To ensure food security in a war-torn economy, the government emphasized cultivation of high yielding varieties (HYV) of rice crop, which required intensive ground water irrigation, usage of chemical fertilizer and pesticides that eventually caused environmental unsustainability [7]. High yielding varieties of rice were first introduced in the country in 1967 and after independence in 1971, growth rate of rice production went up from a meagre 1.6% in 1972 to a lofty 18% in 1973. Despite a noticeable initial success of green revolution, Bangladesh agriculture somewhat fails to sustain its growth potential due to climate change challenges, lack of adoption of more pest and disease resilient rice varieties, less efficient irrigation, and excessive usage of chemical fertilizer [17]. Most recent data indicate a downfall in the growth rate of agricultural value addition from 3.4% in 2020 to 3.2% in 2021[4].

On the other hand, notwithstanding a noticeable decline in total fertility rate, current total population of Bangladesh stands at a staggering 164.7 million, resulting in a population density of 1,265 people per square kilometer and the agricultural sector needs to fulfill the ever-increasing demand for staple food items without sacrificing agricultural sustainability. Bangladesh government is aware of this challenge and the National Environmental Policy (2018) comprises recommendations that encourage sustainable agricultural practices, such as, crop rotation, legume cultivation, and crop diversification for increasing long term agricultural productivity. Although sustainability is a complex notion that involves combination of measurable and unmeasurable indicators, there are three broad dimensions that may incorporate them. These dimensions are environmental, economic, and social in nature and despite the difficulty of gauging them in quantifiable units, 'United Nations Development Program' (UNDP) and 'Food and Agricultural Organization' (FAO) have devised certain measures that can capture their significance. Among these indicators, productivity of agricultural land may capture sustainable growth in this sector, which in turn may positively influence overall sustainable economic growth. This paper employs a multivariate time series methodology to estimate the long run effects of selected indicators of sustainable agriculture on long run farmland productivity of Bangladesh. National data on macroeconomic indicators are utilized for this purpose that are collected from World Development Indicators (WDI) database, which are both readily available, as well as, accessible and therefore, makes it possible for other researchers to replicate the model estimation methodology for other countries as individual case studies.

Most of the research works on sustainable agriculture in relation to Bangladesh are based on primary disaggregated farm level data [12]. These studies have produced valuable observations on the practice of sustainable agriculture and its impacts on agricultural performance at selected farms of rural Bangladesh. However, very few of these seem to have focused on the long run effects of sustainable agriculture or lack of this practice on agricultural growth of the nation. Among these few research works, [4] is worth mentioning, although they have focused on the impacts of unsustainable agricultural practice on environmental degradation. Specifically, the paper finds that producing agricultural crops, such as, rice, and cereal, as well as practices such as, livestock rearing, and land cultivation for cereal production under conventional agriculture increase carbon emission and eventually lead to environmental degradation. [5] evaluated the relationship between twenty-two indicators of sustainable agriculture utilizing the Partial Least Squares (PLS) method applied to a Structural Equation Model (SEM), which is duly estimated using a dataset collected from 357 listed farmers at Teesta Barrage area. The researchers have concluded that ecological, social, and economic indicators of sustainable agriculture are highly and positively correlated with each other. [23] draws attention to the relationship between crop diversity and agricultural sustainability and concludes that a decline in crop diversity reduces agricultural sustainability as well. They have constructed a crop diversity index for Bangladesh and concluded that currently the farmers heavily rely on cultivating few High Yielding Varieties (HYV) of rice that require intensive use of ground water irrigation, usage of chemical fertilizer, and pesticide that eventually reduces environmental sustainability. However, none of the empirical literature focuses on the impact of sustainable agriculture on farmland productivity. On the other hand, the current paper estimates the long run impacts of sustainable and unsustainable agricultural practices in Bangladesh utilizing a multivariate time series model that includes statistical indicators of both. From this standpoint empirical findings of this paper may have significant policy implications as the nation is eyeing on attaining UN announced sustainable development goals by the end of 2030.

## III. CONCEPTUAL FRAMEWORK

Food and Agricultural Organization defines sustainable agricultural practice as the management and conservation of natural resource base and the orientation of technological change such that continued satisfaction of human needs for present and future generations are fulfilled. Accordingly, sustainable agriculture is environmentally non-degrading, technically appropriate, economically viable and socially acceptable, which is supposed to conserve land, water, plant, and animal based genetic resources [10]. In general,



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sustainable agriculture incorporates three broad dimensions, namely environmental, economic, and social. For empirical analysis, it is imperative that we utilize measurable statistical indicators of each of these dimensions.

On the other hand, measures of sustainable agriculture may appear region specific that are likely to evolve in line with changing environmental and socio-economic factors. Hence, it appears to be a daunting task to precisely identify the measures of sustainable agriculture and measure them for the purpose of empirical estimation of an econometric model. In addition, there is no guarantee that a certain agricultural practice will comply with all dimensions of sustainability simultaneously. A certain agricultural activity may appear environmentally and economically sustainable, but it may not be socially sustainable.

Bangladesh has already eyed on attaining the targets of UN set sustainable development goals by 2030. Putting an end to hunger is one of these goals. To attain this goal, the nation needs to ascertain sustainable agricultural practices that will ensure primary food production using resilient means, which simultaneously enhances productivity and conserves eco system by enhancing soil quality in the face of climate change induced natural calamities. According to the UN documents, the indicator of sustainable agriculture is gauged by the 'proportion of agricultural land under productive and sustainable agriculture', which encompasses the environmental, economic, and social dimensions of sustainability. The more disaggregated forms of this indicator involve productivity, profitability, and resilience of land and water resources in agriculture. At this backdrop, it appears immensely important that agricultural sustainability is gauged in terms of quantifiable measures of its three dimensions. [21] mention that a large part of literature focusing on sustainable management of agriculture is guided by the norm 'what gets measured gets managed'.

For empirical analysis this paper deploys annual time series data spanning 1961—2018 on five major aggregative measures of sustainable agriculture in Bangladesh. The paper deliberately utilizes aggregative data on selected indicators of sustainable agriculture presuming that the ensuing empirical outcome may have policy implications of national economic importance. All data are compiled from the 'World Development Indicators' (WDI) databank. Variables are assumed endogenous as these are explained within the estimated model.

Arguably, the first and foremost indicator of sustainable agriculture is productivity of agricultural land. We define this indicator as the agricultural value added in constant 2015 USD per square kilometers of land used in agricultural activities. Higher value added per square kilometers of agricultural land reduces the stress on existing land mass, especially when it is generated by sustainable practices. The amount of arable land is another statistical indicator of sustainable agriculture that we employ estimating our empirical model. 'Food and Agricultural Organization' (FAO) defines arable land as agricultural land cultivated with temporary crops, temporary meadows for mowing, or for pasture. It also includes land under market or kitchen gardens and land that remains temporarily fallow. Different crops have different root systems and when land is cultivated with variegated crops, efficiency of soil fertility increases as plants with deeper root systems bring nutrients from deeper layers of soil to the surface and make these available for plants that use a relatively shallow root network. On the other hand, as arable land is planted with temporary crops, agricultural practices involving this type of land replicates crop rotation, which eventually enhances soil fertility and better pest management on part of the peasants as different crops are vulnerable to different kinds of pests, weeds, and diseases.

Cereal yield per hectare of agricultural land is an important indicator determining the productivity of total agricultural land mass. Cereals include rice, wheat, barley, corn, buckwheat, and other granular seeds that are used for human and animal consumption. These crops constitute the major agricultural output since time immemorial and sustainable cultivation of cereal crops is the main challenge for attaining agricultural sustainability in upcoming days. Considering the food habit of a majority of human population and the importance of a major source of staple food intake of existing global livestock we consider cereal yield per hectare of agricultural land as an important indicator of sustainable agriculture in Bangladesh which is still predominantly agrarian in nature.

The livestock production index is another statistical indicator that we have used estimating our empirical model for analyzing the agricultural sustainability and productivity nexus. Livestock plays a crucial role maintaining agricultural sustainability, especially in developing countries, such as, Bangladesh, where commercial livestock farming is not so prevalent yet. Livestock production system encompasses all three dimensions of sustainability; environmental, economic, and social. For instance, livestock production structure bears the potential of contributing to the preservation of biodiversity. It also contributes to carbon sequestration in soils and biomass and acts as an important source of natural fertilizer, food, income, collateral, and store of wealth. Livestock provides draft animals in places where mechanization is poor and boosts labor productivity.

Lastly, we have considered the usage of inorganic fertilizer as a variable that acts against sustainable agricultural practices. Inorganic or chemical fertilizer products include nitrogenous, potash and phosphate-based fertilizer. These types of fertilizer cause environmental hazards, such as, water and soil pollution, interfere with natural balance of soil microflora and release high levels of nitrate and nitrite in natural source of fresh water and eventually harm human health. In short, usage of inorganic fertilizer is unsustainable as it may enhance soil productivity over the short run at the cost of multidimensional damages inflicted upon environment, nature, and human health condition over a longer time span.

## IV. THEORETICAL CONSTRUCT OF THE MODEL

We assume that productivity of agricultural land in Bangladesh follows a Cobb-Douglas type production function, which involves variables such as, arable land,



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cereal yield, livestock production, and use of chemical fertilizer. We also assume that the production function in this sustainable agricultural setting is captured by an endogenous growth model where the state of technology evolves through research. At this backdrop, the theoretical construct of sustainable productivity in agricultural sector is as follows.

$$y_t = f(A_t, ARB_t, CRLYD_t, LVSTK_t, FRT_t) \;\; .... (1)$$

Equation (1) can be more specifically mentioned in terms of equation (2).

$$y_t = A_t^{\beta_0} + ARB_t^{\beta_1} + CRLYD_t^{\beta_2} + LVSTK_t^{\beta_3} + FRT_t^{\beta_4} \;\; ........... (2)$$

where y_t: value added per square kilometer of agricultural land in year 't'.

〖ARB〗 _t: amount of arable land in agricultural sector in year 't'.

〖CRLYD〗 _t: amount of cereal produced per hectare of agricultural land in year 't'.

〖LVSTK〗 _t: livestock production index in year 't'.

〖FRT〗 _t: kilograms of chemical fertilizer used per hectare of arable land in year 't'.

Equation (2) can be rewritten as follows in natural logarithmic levels of model variables. Equation (2) can be rewritten as follows in natural logarithmic levels of model variables.

$$lny_t = \beta_0 lnA_t + \beta_1 lnARB_t + \beta_2 lnCRLYD_t + \beta_3 lnLVSTK_t + \beta_4 lnFRT_t \;\; ....... (3)$$

Excluding the technology variable, we estimate a reduced form long run equilibrium relationship including the productivity of agricultural land and other indicators of sustainable agriculture in case of Bangladesh.

## V. EMPIRICAL MODEL

The major objective of this paper is to examine if sustainable practice enhances agricultural land productivity. We assume that sustainable agricultural practice requires more time on part of farmers and the desired outcome of this pursuit can be achieved over a longer period. On this ground, we have built a multivariate Vector Error Correction (VEC) model for estimating the long run equilibrium relationship between land productivity in agricultural and four measurable indicators of sustainable agriculture. All variables in a VEC model are endogenous and hence these are treated with equal importance. Initially, we develop a reduced form VAR model in the logarithmic levels of the relevant model variables as follows and we include one lag in these variables for the sake of simplicity.

$$\begin{bmatrix} log\,(y_t) \\ log\,(ARB_t) \\ log\,(CRLYD_t) \\ log\,(LVSTK_t) \\ log\,(FRT_t) \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \\ a_{30} \\ a_{40} \\ a_{50} \end{bmatrix} + \begin{bmatrix} a_{11}\, a_{12}\, a_{13}\, a_{14}\, a_{15} \\ a_{21}\, a_{22}\, a_{23}\, a_{24}\, a_{25} \\ a_{31}\, a_{32}\, a_{33}\, a_{34}\, a_{35} \\ a_{41}\, a_{42}\, a_{43}\, a_{44}\, a_{45} \\ a_{51}\, a_{52}\, a_{53}\, a_{54}\, a_{55} \end{bmatrix} \begin{bmatrix} log\,(y_{t-1}) \\ log\,(ARB_{t-1}) \\ log\,(CRLYD_{t-1}) \\ log\,(LVSTK_{t-1}) \\ log\,(FRT_{t-1}) \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ u_{5t} \end{bmatrix} \;\; ......... (4)$$

With reference to equation/model (4) we developed a Vector Error Correction model as follows.

$$\begin{bmatrix} dlog(y_t) \\ dlog(ARB_t) \\ dlog\,(CRLYD_t) \\ dlog\,(LVSTK_t) \\ dlog\,(FRT_t) \end{bmatrix} = \Gamma_1 \begin{bmatrix} dlogy_{t-1} \\ dlogARB_{t-1} \\ dlogCRLYD_{t-1} \\ dlogLVSTK_{t-1} \\ dlogFRT_{t-1} \end{bmatrix} + \Pi \begin{bmatrix} logy_{t-1} \\ logARB_{t-1} \\ logCRLYD_{t-1} \\ logLVSTK_{t-1} \\ logFRT_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \end{bmatrix} \;\; ....... (5)$$

Model (5) includes current and lagged first differenced endogenous variables in their logarithmic forms. The model also includes lagged logarithmic levels of these variables. All variables in this model are assumed stationary. Lagged variables in their first differences are assumed stationary. The matrix contains the error correction terms (ECT) in a sense that the elements of this matrix are coefficients of long run equilibrium relationships among the variables concerned and the self-correcting adjustment parameters that rectify any deviations from their said long run equilibrium levels. Model (5) can be rewritten as follows that conspicuously shows the ECT terms.

$$\begin{bmatrix} dlog(y_t) \\ dlog(ARB_t) \\ dlog\,(CRLYD_t) \\ dlog\,(LVSTK_t) \\ dlog\,(FRT_t) \end{bmatrix} = \Gamma_1 \begin{bmatrix} dlogy_{t-1} \\ dlogARB_{t-1} \\ dlogCRLYD_{t-1} \\ dlogLVSTK_{t-1} \\ dlogFRT_{t-1} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \\ a_{41} & a_{42} \\ a_{51} & a_{52} \end{bmatrix} \begin{bmatrix} b_{11}\, b_{21}\, b_{31}\, b_{41}\, b_{51} \\ b_{12}\, b_{22}\, b_{32}\, b_{42}\, b_{52} \end{bmatrix} \begin{bmatrix} log(y_{t-1}) \\ log(ARB_{t-1}) \\ log(CRLYD_{t-1}) \\ log(LVSTK_{t-1}) \\ log(FRT_{t-1}) \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \end{bmatrix} \;\; .... (6)$$

For the sake of further clarification, we may focus on the error correction part of the first equation of model (6) as follows ignoring the error terms for simplification.

$$\Pi \begin{bmatrix} logy_{t-1} \\ logARB_{t-1} \\ logCRLYD_{t-1} \\ logLVSTK_{t-1} \\ logFRT_{t-1} \end{bmatrix} = a_{11}(b_{11}logy_{t-1} + b_{21}logARB_{t-1} + b_{31}logCRLYD_{t-1} + b_{41}logLVSTK_{t-1} + b_{51}logFRT_{t-1}) + a_{12}(b_{12}logy_{t-1} + b_{22}logARB_{t-1} + b_{32}logCRLYD_{t-1} + b_{42}logLVSTK_{t-1} + b_{52}logFRT_{t-1}) \;\; .... (7)$$

The first two equations on the right-hand side of (7) reflect the two cointegrating equations along with their speed of adjustment parameters and respectively.



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**Data description and Unit Root test outcome**

For empirical analysis this paper estimates an unrestricted VAR model in the logarithmic levels of variables including agricultural land productivity, arable land, livestock production, usage of inorganic fertilizer, and cereal yield, which are also the statistical indicators of sustainable agriculture. Annual time series data on these variables spanning 1961—2018 are obtained from 'World Development Indicators' databank. Year specific dummy variables are used to neutralize the undesirable effects of residual outliers on estimation outcome. Table 1 shows the detailed data description, data sources and variable abbreviations that are used to estimate the empirical models. For estimating the multivariate time series models, such as VAR and VEC, it is imperative that we check the order of integration of relevant model variables. We conduct the Augmented Dickey Fuller (ADF) test for all model variables for this purpose. Table 2 compiles the ADF test outcomes.

Table 1: Variables and Data sources

| *Variables* | *Acronyms* | *Measurement* | *Data Source* |
|---|---|---|---|
| Productivity of agricultural land | $AGLNDPRD_t$ | Constant 2015 US dollars per square kilometer | Calculated from data procured from World Development Indicators (WDI) Databank |
| Land under temporary crops | $ARABLAND_t$ | Hectares | WDI Databank |
| Cereal productivity of land | $CEREALYIELD_t$ | Kilograms per hectare | WDI Databank |
| Usage of inorganic fertilizer in agriculture | $FERTILIZERUSE_t$ | Kilograms per hectare of arable land. | WDI Databank |
| Livestock production | $LIVESTOCKPRDN_t$ | Index number (2014—2016 = 100) | WDI Databank |

We proceed by plotting the data series on all model variables in their logarithmic levels to inspect if these exhibit some definite time trends and/or deterministic components. Expressing data in logarithm has the advantage of eliminating any nonlinearity if there is any. In addition, logarithmic conversion of level data allows us to interpret estimated coefficients of the normalized cointegrating equation in terms of percentage change in the response variable due to one percentage change (either positive or negative) in the right-hand side source variable in consideration.

Figure 1: Logarithmic level of agricultural land productivity (1961--2018)

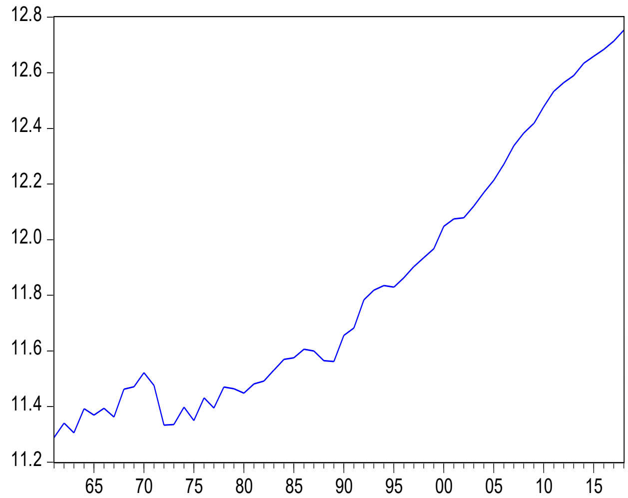



Figure 2: Logarithmic level data on hectares of arable land (1961--2018)

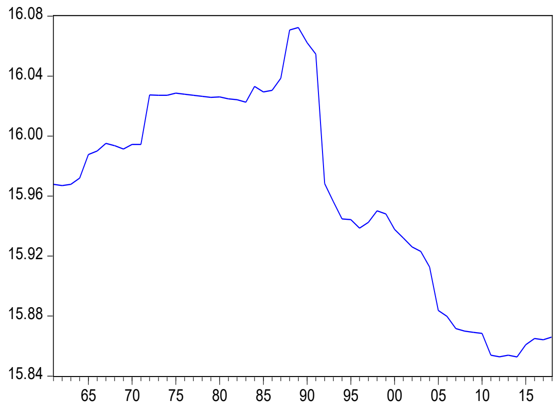
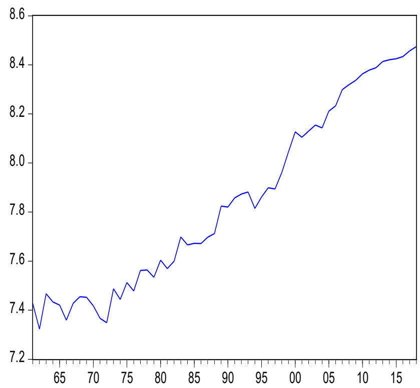



Figure 3: Logarithmic level of cereal yield in kilograms per hectare of arable land (1961--2018)




Visual inspection of figure 1, 3, 4, and 5 reveals these data series have conspicuous positive time trends with positive vertical intercepts. Figure 2 on the other hand, shows a drifting behavior without any definite positive or negative trending behavior.



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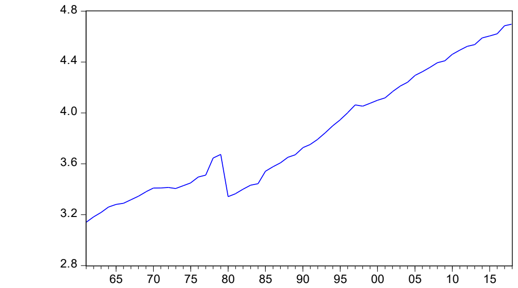
Figure 5: Logarithmic level of livestock production index (2014--2016=100), data range: 1961--2018




Following the visual inspection of logarithmic level data on model variables, we utilize the specific Augmented Dickey Fuller (ADF) test equation (8) for checking the order of integration in log-level data series of all model variables.

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + \alpha_1 t + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + u_t \text{ ……… (8)}$$

Equation (8) specifies a time series variable in its first difference, which includes a deterministic time trend 't', a vertical intercept , an augmentation term with a lag length equals '$p$' and a stochastic error term . The null hypothesis of this test states that the level data series has a unit root against the alternative that the data series does not contain a unit root. On the other hand, the null hypothesis of this test also states that the first differenced data series contains a unit root against the alternative that such a data series does not contain a unit root. If a data series contain a unit root, it is said to be nonstationary, signifying a variable time trend. In contrast, if a data series is found stationary it will signify a constant time invariant trend value.

Table 2 reports the unit root test outcome. All model variables in their logarithmic levels are tested for unit roots. The presence of unit roots in time series data is indicative of their non-stationarity. All data series are visually examined if they show any trending behavior and consequently assigned trend and intercept components in their ADF test equations. Table 2 shows that all model variables contain unit roots in their logarithmic levels or in other words, all of these are non-stationary in their logarithmic levels but prove stationary in their first differences. In other words, the null hypothesis of a unit root cannot be rejected in the logarithmic levels of these variables, but in their logarithmic first differences the null hypothesis of a unit root is strongly rejected at 1% level of significance. Therefore, it may be concluded that all model variables are integrated of order 1, or alternatively I (1), as these are non-stationary in their logarithmic levels, but stationary in their logarithmic first differences. Hence, we conclude that the model variables are integrated of the same order.

Table 2: ADF Test results for Unit Root

| Variables | Levels | | | | First Difference | | | |
|---|---|---|---|---|---|---|---|---|
| | ADF Test statistic | Trend | Intercept | p-value | ADF Test statistic | Trend | Intercept | p-value |
| Log ($AGLNDPRD_t$) | -1.12 | Yes | Yes | 0.92 | -7.91*** | No | Yes | 0.00 |
| Log ($ARABLAND_t$) | -0.16 | No | Yes | 0.94 | -5.80*** | No | No | 0.00 |
| Log ($CEREALYIELD_t$) | -3.44 | Yes | Yes | 0.06 | -11.2*** | No | Yes | 0.00 |
| Log ($FERTILIZERUSE_t$) | -2.36 | Yes | Yes | 0.40 | -7.58*** | No | Yes | 0.00 |
| Log ($LIVESTOCKPRDN_t$) | -1.85 | Yes | Yes | 0.67 | -7.29*** | No | Yes | 0.00 |

Note: *** denotes 1% level of significance

**VAR Model selection, estimation, and diagnostic tests**

For empirical analysis, we estimate a VAR model in the logarithmic levels of variables in consideration. The VAR model consists of simultaneous equations, each of which expresses every endogenous variable in terms of its own past values and those of other endogenous variables included in the model. The advantage of a VAR model is that all variables are endogenous and therefore these are treated in equal footing and consequently the model avoids complicacy of preselecting variables into two distinct groups, such as 'endogenous' and 'exogenous.' In this sense, a VAR model avoids the 'biasness' that may arise because of categorizing some variables as 'independent' and others as 'dependent' by the very way it is constructed. Each individual equation in the VAR model is estimated independently using the OLS method.

However, our level VAR model is susceptible to producing spurious regression coefficients as these are estimated by the OLS method applied to each individual equation that includes nonstationary variables. By nature, the spurious regression coefficients are overly statistically significant as their standard deviations are underestimated due to the nonstationary nature of model variables. Hence, we start the data analysis part of this paper with the 'unit root' test to detect the stationarity status of variables and to determine their order of integration. Augmented Dickey Fuller (ADF) test is conducted for this purpose. All variables are found non-stationary in their logarithmic levels and stationary in their first differences at 5% level of significance with the implication that all of these are integrated of order one. Consequently, a VAR model is estimated in the logarithmic levels of relevant model variables and Johansen-Juselius (1988, 1992) cointegration test is conducted for detecting any cointegrating relationship among these non-stationary variables. According to this test, if there exists a cointegrating relationship among the non-stationary variables, it represents a long run equilibrium relationship that proves to be stationary.

Finally, we estimate a VAR model in the logarithmic levels of variables using a balanced sample of annual observations spanning 1961-2018. Considering a rather limited amount (57 observations) of time series data, the primitive level VAR model is estimated using a relatively small number of lags (=5). VAR (5) is found stable, but as the test for residual heteroskedasticity cannot be conducted due to the presence of negative numbers in the test equation, four lags



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are used for re-estimating the initial VAR model. VAR (4) is found stable as the largest root of the autoregressive characteristic polynomial of this model equals 0.9915 and hence proves less than unity. Table 3 reports the lag selection test outcome for the level VAR model. According to lag selection test outcome, VAR (4) is supported by AIC criterion that attains the lowest value for this lag length. Eventually, four lags are used for estimating the initial level VAR model. Conventionally, lag length in VAR model is selected by AIC or SC criterion.

Table 3: Lag selection criteria in the level VAR model

Sample: 1961—2018

Number of observations: 57

| Lag | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|
| 0 | NA | 5.82e-10 | -7.096890 | -5.255238 | -6.386637 |
| 1 | 595.74 | 3.60e-16 | -21.44627 | -18.68379* | -20.38089 |
| 2 | 49.10 | 2.39e-16 | -21.96434 | -18.28104 | -20.54384 |
| 3 | 43.20* | 1.66e-16* | -22.52799 | -17.92386 | -20.75236* |
| 4 | 26.26 | 1.94e-16 | -22.69628* | -17.17132 | -20.56552 |

Note: Indicates significant at 5% level of significance

We have also conducted the lag exclusion test to check if we can pare down the lag length in our level VAR (4) model. Table 4 reports the lag exclusion test outcome for estimated VAR (4) model. Each column shows the Chi-square test statistic and its corresponding p-value in relation to the null hypothesis that lag of the relevant endogenous variable in that equation of VAR model equals zero. For instance, the first column of table 4 shows the Chi-square test statistic values for lag 1, lag 2, lag 3, and lag 4 for other endogenous variables in log (AGLNDPRD) equation of VAR (4) model. In this equation, the null hypothesis that lags 1 and 2 of other variables in this equation can be rejected as the p-value of the corresponding Chi-square test statistic are equal to zero.

associated p-value of zero. Hence, the null hypothesis can be rejected and lag 1 proves significant. Similarly, lags 2 and 3 also prove statistically significant in the estimated VAR (4) model. However, lag 4 appears statistically significant at 10% level of significance.

After estimating VAR (4) model, we conducted the residual normality test for this model. Table 5 shows residual normality test outcome for VAR (4), which does not indicate significant Skewness and Kurtosis. Overall, the residuals of the estimated VAR (4) model are normally distributed.

Table 6: Residual serial correlation LM test for VAR (4)

: No residual serial correlation at the chosen lag

| Lags | LM statistic | p-value |
|---|---|---|
| 1 | 39.98761 | 0.0292 |
| 2 | 16.64920 | 0.8941 |
| 3 | 18.52359 | 0.8194 |
| 4 | 12.80775 | 0.9788 |
| 5 | 10.52186 | 0.9950 |
| 6 | 30.22811 | 0.2159 |

Table 6 reports residual serial correlation test outcomes for VAR (4) model. For each lag of the estimated VAR model, the LM statistic value and the corresponding probability is reported. The null hypothesis of no serial correlation at lag 1 is rejected as the probability value of the LM statistic for this lag is less than 5%. Hence, the null hypothesis of an absence of residual autocorrelation is rejected for this lag. However, the LM statistic value for lag 4 is 12.81 with a corresponding probability value of 0.98. Hence, the null hypothesis of no residual autocorrelation for this lag cannot be rejected.

Table 4: VAR Lag Exclusion Wald Tests

Included observations: 54

Joint Null Hypothesis: estimated parameters of lag 4 are zero in all equations of VAR (4)

Chi-squared test statistics for lag exclusion:

Numbers in [ ] are p-values

| | LOG(AGLNDPRD) | LOG(ARABLAND) | LOG(CEREALYIELD) | LOG(FERTILIZERUSE) | LOG(LIVESTOCKPRDN) | Joint |
|---|---|---|---|---|---|---|
| Lag 1 | 106.1358 | 189.3293 | 17.04956 | 33.79366 | 160.5229 | 562.9892 |
| | [ 0.000000] | [ 0.000000] | [ 0.004407] | [ 2.62e-06] | [ 0.000000] | [ 0.000000] |
| Lag 2 | 32.05862 | 1.544882 | 4.645643 | 3.183660 | 0.705422 | 58.44468 |
| | [ 5.78e-06] | [ 0.907833] | [ 0.460636] | [ 0.671695] | [ 0.982670] | [ 0.000171] |
| Lag 3 | 7.268870 | 3.271721 | 5.710021 | 15.65836 | 0.775020 | 48.23952 |
| | [ 0.201400] | [ 0.658174] | [ 0.335465] | [ 0.007890] | [ 0.978599] | [ 0.003491] |
| Lag 4 | 2.725113 | 2.797858 | 21.19994 | 6.801193 | 2.937847 | 34.96860 |
| | [ 0.742275] | [ 0.731116] | [ 0.000743] | [ 0.235851] | [ 0.709568] | [ 0.088773] |
| df | 5 | 5 | 5 | 5 | 5 | 25 |

The last column of this table shows Chi-square test statistic values of the joint null hypothesis that a certain lag for all endogenous variables in all equations of VAR (4) are jointly equal to zero. For instance, the first entry of the last column of this table shows that Chi-square value (=562.99) of the joint null hypothesis that lag 1 of all endogenous variables in all equations of VAR (4) are equal to zero with the

**Cointegration test outcome for level VAR (4) model**

Table 7 reports the outcome of Johansen-Juselius test for detecting cointegrating relationships in VAR (4)
model. Both Trace and maximum Eigenvalue tests detect two cointegrating relationships at 5 percent level of significance. Both tests identify the cointegrating relationships specified by model 3 that allows deterministic

trends in data and an intercept in the cointegrating equations.

Table 7: Johansen-Juselius cointegration test outcome
Sample (adjusted): 1965--2018, Included observations: 54 after adjustments
Lags interval (in first differences): 1 to 3

| Maximum rank | | 5% critical value | | 5% critical value |
|---|---|---|---|---|
| $r = 0$ | 101.88 | 68.52 | 44.80 | 33.46 |
| $r = 1$ | 57.08 | 47.21 | 31.69 | 27.07 |
| $r = 2$ | 25.39** | 29.68 | 16.78* | 20.97 |
| $r = 3$ | 8.61 | 15.41 | 8.33 | 14.07 |

**Estimation of the Vector Error Correction Model:**

Since the initial VAR (4) model is estimated using 4 lags in the logarithmic levels of variables concerned, the multivariate counterpart of the (Engle-Granger) error correction model (VECM) is estimated using 3 lags of these variables. One lag disappears due to first differencing the log-level data series that accounts for the short run part of the VECM. The VECM (3) model is duly estimated by normalizing the long run part for logarithmic level of 'agricultural land productivity' variable in terms of others. Subsequently, we impose zero restrictions on the short run adjustment parameters. The restrictions identify all cointegrating vectors. Table 8 reports outcomes of the LR (Log-Likelihood ratio) test for the binding restrictions imposed on VECM (3).

Table 8: Loglikelihood Ratio (LR) test for binding restrictions imposed on VECM (3)

| | |
|---|---|
| LR test for binding restrictions (rank = 1): Restrictions imposed on the cointegrating vector is valid | |
| Cointegrating restrictions: B (1,1)=1, A(1,1)=0, A(2,1)=0, A(5,1)=0 | p-value = 0.105 |

Note: Convergence achieved after 108 iterations
Restrictions identify all cointegrating vectors

**Implications of the cointegrating restrictions:**

B (1,1) =1 implies that the first cointegrating equation of VECM (3) is normalized for the first endogenous variable, i.e., the left-hand side of this equation reports logarithmic level of productivity of agricultural land and the right-hand side variables are logarithmic levels of cereal yield, usage of inorganic fertilizer, arable land, and livestock production index. The estimated normalized long run equilibrium relationship is as follows.

$$logAGLNDPRD_{t-1} = ECT_t + 6.05logARABLAND_{t-1} + 0.79logCEREALYIELD_{t-1} - 0.49logFERTILIZERUSE_{t-1} + 1.9logLIVESTOCKPRDN_{t-1} + \varepsilon_t$$

…………… (9)

| Table 9: Estimated coefficients of the non-normalized cointegrating equation | | | |
|---|---|---|---|
| | | | |
| -6.05*** (1.75) | -0.79* (0.55) | 0.49*** (0.10) | -1.90*** (0.52) |
| Note: t-statistic values are in brackets and standard errors are in parentheses | | | |
| , 10% level of significance. , 1% level of significance. | | | |

where
AGLNDPRD: productivity of agricultural land.
ARABLAND: total amount of arable land.
CEREALYIELD: cereal yield.
FERTILIZERUSE: usage of inorganic fertilizer in agriculture.
LIVESTOCKPRDN: livestock production index.

Equation (9) is the estimated normalized long run cointegrating (equilibrium) relationship between the model variables. It is visible that except for the 'fertilizer use', other model variables have positive long run impacts on the productivity of agricultural land. On the other hand, except for the cereal yield, other indicators of sustainable agriculture are statistically significant at 1% level of significance. In addition, the long run positive impact of cereal yield on agricultural land productivity is significant at 10% level of significance. Table 10 reports short run analysis of the estimated VECM (3). However, not all (error correction terms) attain their expected negative algebraic signs.

According to Johansen-Juselius (1992) methodology, the term in VEC model must be negative so that once the relationship between nonstationary model variables deviates from their cointegrating relationship last year, the deviation gets rectified in current year as the cointegration is restored. However, this is not the case for VEC (3) that we have estimated. More specifically, the speed of adjustment parameter attached to first cointegrating relationship in the first equation of VECM (3), i.e. A (1,1) fails to attain this negative sign and so do the adjustment parameters for the first cointegrating equation in the second and fifth equations of VECM (3).



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Table 10: Analysis of the short run part of VECM (3) model with no restrictions on the short run part

| Restrictions imposed: b (1,1) =1, no restrictions on Error Correction Terms (ECT) | Current Endogenous Variables in First Differenced Logarithmic Terms | | | | |
|---|---|---|---|---|---|
| | $\Delta\log(AGLNDPRD_t)$ | $\Delta log(ARABLAND_t)$ | $\Delta log(CEREALYIELD_t)$ | $\Delta log(FERTILIZERUSE_t)$ | $\Delta log(LIVESTOCKPRDN_t)$ |
| Lagged Endogenous Variables in Differences | | | | | |
| Intercept | 0.015697 (0.00709)[ 2.21435] | -0.00004 (0.00236) [-0.01688] | 0.058890 (0.01396) [ 4.21805] | 0.083359 (0.03417) [ 2.43973] | 0.026680 (0.00840) [ 3.17747] |
| $\Delta\log(AGLNDPRD_{t-1})$ | -0.159495 (0.14858) [-1.07349] | -0.009190 (0.0495) [-0.18558] | -0.228623 (0.29263) [-0.78128] | 3.086391 (0.71613) [ 4.30982] | -0.117237 (0.17599) [-0.66616] |
| $\Delta\log(AGLNDPRD_{t-2})$ | 0.337128 (0.18615) [ 1.81109] | 0.022903 (0.06204) [ 0.36917] | 0.658786 (0.36662) [ 1.79691] | 2.648380 (0.89722) [ 2.95177] | -0.194681 (0.22049) [-0.88294] |
| $\Delta\log(AGLNDPRD_{t-3})$ | -0.031254 (0.11765) [-0.26564] | -0.027946 (0.0392) [-0.71266] | 0.425800 (0.23173) [ 1.83752] | 0.580026 (0.56709) 1.02281] | -0.096509 (0.13936) [-0.69250] |
| $\Delta log(ARABLAND_{t-1})$ | -0.300721 (0.24291) [-1.23797] | 0.117435 (0.08096) [ 1.45052] | 0.267510 (0.47843) [ 0.55914] | 2.907467 (1.17084) [ 2.48324] | -0.307215 (0.28773) [-1.06770] |
| $\Delta log(ARABLAND_{t-2})$ | 0.457885 (0.25607) [ 1.78814] | 0.125484 (0.08534) [ 1.47033] | 1.083976 (0.50433) [ 2.14933] | 0.476616 (1.23423) [ 0.38616] | -0.122868 (0.30331) [-0.40509] |
| $\Delta log(ARABLAND_{t-3})$ | -0.047810 (0.23091) [-0.20705] | -0.019674 (0.07696) [-0.25564] | 0.175027 (0.45478) [ 0.38486] | -0.577825 (1.11297) [-0.51917] | -0.240037 (0.27351) [-0.87760] |
| $\Delta log(CEREALYIELD_{t-1})$ | 0.531230 (0.07894) [ 6.72915] | -0.040302 (0.02631) [-1.53172] | -0.329199 (0.15548) [-2.11726] | -1.135895 (0.38051) [-2.98520] | 0.011769 (0.09351) [ 0.12586] |
| $\Delta log(CEREALYIELD_{t-2})$ | -0.078074 (0.10852) [-0.71941] | -0.006530 (0.03617) [-0.18055] | -0.030773 (0.21374) [-0.14397] | -1.705293 (0.52308) [-3.26008] | 0.130700 (0.12855) [ 1.01673] |
| $\Delta log(CEREALYIELD_{t-3})$ | -0.030727 (0.11600) [-0.26488] | -0.031979 (0.03866) [-0.82712] | -0.567785 (0.22847) [-2.48512] | -1.308224 (0.55913) [-2.33974] | 0.153265 (0.13741) [ 1.11540] |
| $\Delta log(FERTILIZERUSE_{t-1})$ | 0.002017 (0.02927) [ 0.06892] | 0.001287 (0.00976) [ 0.13196] | -0.123500 (0.05765) [-2.14216] | -0.069058 (0.14109) [-0.48947] | 0.019238 (0.03467) [ 0.55486] |
| $\Delta log(FERTILIZERUSE_{t-2})$ | 0.017305 (0.02309) [ 0.74938] | 0.007115 (0.00770) [ 0.92441] | -0.099864 (0.04548) [-2.19567] | -0.127070 (0.11131) [-1.14162] | 0.016148 (0.02735) [ 0.59034] |
| $\Delta log(FERTILIZERUSE_{t-3})$ | -0.000489 (0.02527) [-0.01937] | -0.000112 (0.00842) [-0.01332] | -0.123938 (0.04978) [-2.48980] | 0.172510 (0.12182) [ 1.41611] | 0.015297 (0.02994) [ 0.51097] |
| $\Delta log(LIVESTOCKPRDN_{t-1})$ | 0.083626 (0.05906) [ 1.41603] | 0.003915 (0.01968) [ 0.19891] | 0.004278 (0.11631) [ 0.03678] | -0.684725 (0.28465) [-2.40549] | 0.038357 (0.06995) [ 0.54832] |
| $\Delta log(LIVESTOCKPRDN_{t-2})$ | -0.075905 (0.06020) [-1.26082] | 0.018191 (0.02006) [ 0.90663] | -0.086074 (0.11857) [-0.72592] | -0.728159 (0.29017) [-2.50939] | 0.042249 (0.07131) [ 0.59247] |
| $\Delta log(LIVESTOCKPRDN_{t-3})$ | 0.026561 (0.06048) [ 0.43920] | 0.000592 (0.02016) [ 0.02939] | -0.296879 (0.11911) [-2.49252] | -0.750861 (0.29149) [-2.57596] | 0.040104 (0.07163) [ 0.55985] |
| $ECT_{t-1}$ | 0.004815 (0.03508) [ 0.13725] | 0.009613 (0.01169) [ 0.82220] | -0.151474** (0.06909) [-2.19239] | -0.828954*** (0.16908) [-4.90266] | 0.061093 (0.04155) [ 1.47027] |
| $R^2$ | 0.899631 | 0.912029 | 0.642548 | 0.792789 | 0.917398 |
| Log likelihood | 734.2586 | | | | |
| Residual Normality Test | $\chi^2(df)$, $H_0$: *residuals are multivariate normal* | | | | |
| | Skewness: 6.31(5), Prob.= 0.28 | Kurtosis: 4.95(5), Prob.= 0.42 | Jarque-Bera: 11.26(10) Prob.=0.34 | | |
| Residual Serial Correlation LM Test | LM -Stat (Prob.), $H_0$: No serial correlation at the chosen lag length | | | | |
| | Lags: | 1 | 2 | 3 | 4 |
| | LM -Stat (Prob.) | 28.82 (0.27) | 17.27 ( 0.87) | 20.68 ( 0.71) | 15.76 ( 0.92) |
| Residual Heteroskedasticity Test | $\chi^2(df)$, $H_0$: No residual Heteroskedasticity<br>Joint Test: $\chi^2(615) = 575.41$, Prob. = 0.87 | | | | |

second and fifth equations of VECM (3).

Note: Figures in parentheses are standard errors of the estimated coefficients and in brackets are their 't statistic' values in the model estimation part, ***indicates 1% level of statistical significance, **indicates 5% level of statistical significance, statistical significance of ECT terms are shown only.

Consequently, the VEC (3) model is re-estimated by normalizing the cointegrating equation for logarithmic level of agricultural land productivity and after imposing zero restrictions on the speed of adjustment parameters associated with the first, second and fifth short run parts of the model. Table 11 displays the estimation outcome of the restricted VECM (3) model. The 'Log-likelihood ratio' (LR) test is conducted to check if the restrictions are binding. Chi-square statistic of this test equals 6.15 with 3 'degrees of freedom' with an associated probability value of 0.104. The null hypothesis of this test states that the zero restrictions imposed on the 'error correction terms' (ECT) are binding and valid. Hence, the null hypothesis cannot be rejected as the probability of committing the type I error in such a case appears more than 10%.

**Sensitivity analysis:**

Sensitivity analysis of the residual behavior of VEC (3) model demonstrates that residuals of this model are multivariate normal and do not exhibit statistically significant Skewness and Kurtosis. Residual autocorrelation LM test detects no significant residual serial correlation from lag 1 to 5 for this model. Finally, the estimated model does not show any significant residual heteroskedasticity.

Figure 6: Cointegration Graph of the Unrestricted VEC (3) Model

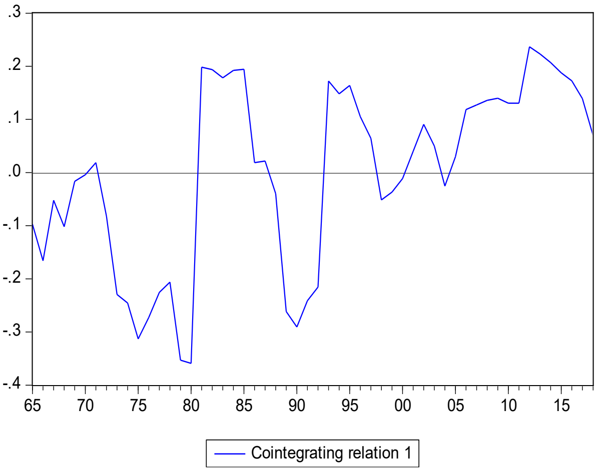


Figure 7: Cointegration Graph of the Restricted VEC (3) Model

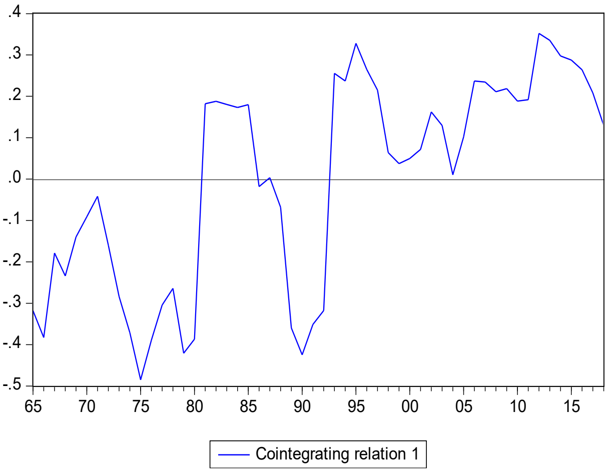


Table 11: Analysis of the short run part of restricted VECM (3) model

Cointegration Restrictions: B (1,1) =1, A (1,1) =0, A (2,1) =0, A (5,1) =0
Restrictions identify all cointegrating vectors, LR test for binding restrictions (rank = 1):
$\chi^2(3) = 6.15$, Probability= 0.104

| | Current Endogenous Variables in First Differenced Logarithmic Terms | | | | |
|---|---|---|---|---|---|
| Lagged Endogenous Variables in Differences | $\Delta\log(AGLNDPRD_t)$ | $\Delta log(ARABLAND_t)$ | $\Delta log(CEREALYIELD_t)$ | $\Delta log(FERTILIZERUSE_t)$ | $\Delta log(LIVESTOCKPRDN_t)$ |
| Intercept | 0.015293 (0.00718) [ 2.13147] | -0.00003 (0.00242) [-0.01120] | 0.059957 (0.01504) [ 3.98538] | 0.105256 (0.03343) [ 3.14837] | 0.025466 (0.00860) [ 2.96021] |
| $\Delta\log(AGLNDPRD_{t-1})$ | -0.163632 (0.14551) [-1.12455] | -0.000491 (0.04914) [-0.00999] | -0.339421 (0.30509) [-1.11252] | 2.812803 (0.67799) [ 4.14874] | -0.088800 (0.17446) [-0.50900] |
| $\Delta\log(AGLNDPRD_{t-2})$ | 0.310766 (0.18279) [ 1.70015] | 0.048253 (0.06172) [ 0.78176] | 0.380139 (0.38326) [ 0.99187] | 2.653688 (0.85169) [ 3.11580] | -0.157024 (0.21916) [-0.71649] |
| $\Delta\log(AGLNDPRD_{t-3})$ | -0.039888 (0.11477) [-0.34755] | -0.017560 (0.03876) [-0.45309] | 0.304941 (0.24064) [ 1.26720] | 0.460662 (0.53476) [ 0.86143] | -0.074234 (0.13761) [-0.53947] |
| $\Delta log(ARABLAND_{t-1})$ | -0.299237 (0.24236) [-1.23468] | 0.119211 (0.08184) [ 1.45663] | 0.237675 (0.50816) [ 0.46771] | 2.720924 (1.12926) [ 2.40947] | -0.294046 (0.29058) [-1.01193] |
| $\Delta log(ARABLAND_{t-2})$ | 0.451118 (0.25376) [ 1.77771] | 0.135839 (0.08569) [ 1.58521] | 0.957784 (0.53207) [ 1.80010] | 0.254320 (1.18239) [ 0.21509] | -0.094841 (0.30425) [-0.31172] |
| $\Delta log(ARABLAND_{t-3})$ | -0.028524 (0.23567) [-0.12103] | -0.029416 (0.07958) [-0.36963] | 0.253794 (0.49415) [ 0.51360] | -1.093492 (1.09811) [-0.99580] | -0.225573 (0.28256) [-0.79831] |
| $\Delta log(CEREALYIELD_{t-1})$ | 0.528051 (0.07918) [ 6.66935] | -0.038573 (0.02674) [-1.44271] | -0.343930 (0.16601) [-2.07174] | -1.058030 (0.36891) [-2.86795] | 0.009971 (0.09493) [ 0.10504] |
| $\Delta log(CEREALYIELD_{t-2})$ | -0.070863 (0.10707) [-0.66184] | -0.014441 (0.03616) [-0.39941] | 0.059319 (0.22450) [ 0.26423] | -1.649969 (0.49888) [-3.30731] | 0.115739 (0.12837) [ 0.90158] |
| $\Delta log(CEREALYIELD_{t-3})$ | -0.016500 (0.11612) [-0.14209] | -0.044432 (0.03921) [-1.13312] | -0.434841 (0.24348) [-1.78595] | -1.382450 (0.54107) [-2.55504] | 0.138800 (0.13923) [ 0.99693] |
| $\Delta log(FERTILIZERUSE_{t-1})$ | 0.006112 (0.03124) [ 0.19566] | -0.000488 (0.01055) [-0.04623] | -0.110943 (0.06549) [-1.69392] | -0.195580 (0.14555) [-1.34377] | 0.023708 (0.03745) [ 0.63304] |
| $\Delta log(FERTILIZERUSE_{t-2})$ | 0.019565 (0.02396) [ 0.81669] | 0.007313 (0.00809) [ 0.90395] | -0.109662 (0.05023) [-2.18322] | -0.265328 (0.11162) [-2.37702] | 0.024233 (0.02872) [ 0.84370] |
| $\Delta log(FERTILIZERUSE_{t-3})$ | 0.002686 (0.02693) [ 0.09975] | -0.000254 (0.00909) [-0.02798] | -0.131739 (0.05646) [-2.33313] | 0.002611 (0.12548) [ 0.02081] | 0.024656 (0.03229) [ 0.76362] |
| $\Delta log(LIVESTOCKPRDN_{t-1})$ | 0.084747 (0.05550) [ 1.52704] | -0.001564 (0.01874) [-0.08343] | 0.078653 (0.11636) [ 0.67592] | -0.429119 (0.25859) [-1.65947] | 0.015754 (0.06654) [ 0.23676] |
| $\Delta log(LIVESTOCKPRDN_{t-2})$ | -0.072489 (0.05661) [-1.28040] | 0.011840 (0.01912) [ 0.61930] | -0.006390 (0.11871) [-0.05383] | -0.550540 (0.26379) [-2.08702] | 0.022733 (0.06788) [ 0.33490] |
| $\Delta log(LIVESTOCKPRDN_{t-3})$ | 0.028979 (0.05711) [ 0.50744] | -0.005199 (0.01928) [-0.26959] | -0.222076 (0.11974) [-1.85463] | -0.549866 (0.26609) [-2.06644] | 0.020110 (0.06847) [ 0.29370] |
| $ECT_{t-1}$ | 0.000000 | 0.000000 | -0.023002 (0.04361) [-0.52747] | -0.563785*** (0.10066) [-5.60085] | 0.000000 |
| $R^2$ | 0.90 | 0.91 | 0.60 | 0.81 | 0.92 |
| Log likelihood | 731.18 | | | | |
| Residual Normality Test<br>Degrees of freedom are in parentheses | $\chi^2(df)$, $H_0$: *residuals are multivariate normal* | | | | |
| | Skewness:6.90(5), Prob. = 0.23 | Kurtosis: 2.08(5), Prob. = 0.84 | Jarque-Bera: 8.98(10), Prob. = 0.53 | | |
| Residual Serial Correlation LM Test | LM -Stat (Prob.), $H_0$: No serial correlation at the chosen lag length | | | | |
| Lags: | 1 | 2 | 3 | 4 | 5 |
| LM -Stat (Prob.), probability values are in parentheses | 33.33 ( 0.12) | 28.51 ( 0.29) | 24.72 ( 0.48) | 22.01 ( 0.64) | 19.47 ( 0.77) |
| Residual Heteroskedasticity Test | $\chi^2(df)$, $H_0$: No residual Heteroskedasticity | | | | |
| Degrees of freedom are in parenthesis | Joint Test: $\chi^2(615) = 562.84$, Prob. = 0.93, degrees of freedom are in parenthesis | | | | |

Note: Figures in parentheses are standard errors of the estimated coefficients and in brackets are their 't statistic' values in the model estimation part, ***indicates 1% level of statistical significance, **indicates 5% level of statistical significance, statistical significance of ECT terms are shown only.



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Figure 8 displays the impulse responses of logarithmic levels of agricultural land productivity due to one standard deviation positive shock to the indicators of sustainable agriculture in Bangladesh, namely, logarithmic levels of arable land, cereal yield, fertilizer use, and livestock production index. Except for arable land, impulse responses of agricultural land productivity exhibit expected dynamic behavior. The first graph in figure 3 shows that logarithmic level of agricultural land productivity declines due to an unexpected positive shock to arable land in the first year but increases thereafter. The second graph shows that agricultural land productivity immediately responds positively due to a positive shock to cereal yield. The third graph shows that agricultural land productivity experiences a prolonged downfall due to a positive shock to the usage of inorganic fertilizer use and the last graph indicates that a positive shock to livestock production index results in a prolonged positive impact on agricultural land productivity as expected. Therefore, the simulation analysis of the empirical model of this thesis are in support of the theoretical predictions of the dynamic behavior of agricultural land productivity due to sustainable agricultural practices in Bangladesh.

## VI. CONCLUSION

Bangladesh is committed to attain sustainable development goals by 2030 and sustainable agriculture is one of the most important of these goals given the agrarian nature of this economy. At this backdrop, this paper effectively employs a multivariate error correction model (VEC) and estimates the long run impacts of some measurable indicators of sustainable agriculture on agricultural land productivity and found plausible responses in line with theoretical literature. More specifically, our empirical findings reflect that a 1 percent increase in the amount of arable land and cereal yield leads to 6.05% and 0.79% increase in agricultural land productivity respectively over the long run. On the other hand, a 1% increase in livestock production leads to a 1.9% increase in agricultural land productivity, but the same increase in inorganic fertilizer use leads to a 0.49% decrease in agricultural land productivity over the long run. Except for one, all estimated long run coefficients of the farmland productivity model due to 1% change (increase or decrease) in sustainable agricultural practice are found statistically significant at 1% level of significance.

These empirical findings may have important policy implications. We may deduce that government should encourage farmers to conserve their arable land or discourage them from using this land for unsustainable use, such as shrimp culture in coastal areas by trapping brackish water from nearby estuarian rivers. The government should also encourage the farmers to cultivate high yielding varieties of cereal through agricultural extension services and allocate more funds to national research facilities for developing high yielding cereal varieties. There should be government financed initiatives for discouraging the usage of chemical fertilizer that may eventually leach into nearby fresh water sources, seep into the depth of arable land and contaminate ground water table.

Most of the research papers focus on estimating empirical models using primary data on sustainable agricultural indicators. While primary data are collected from candid interviews with farmers that may have more appeal to readers, estimated models using these data may lose the much-required generalization that can be attained from models that are estimated using more aggregated national level data. Further research can be done focusing on this issue.

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